



## Wind resource assessment and wind power forecasting

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Chapter 10

# Wind resource assessment and wind power forecasting

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What will be the cornerstone of grid operators, balance responsible parties, energy policymakers, investors and traders in future energy systems with large shares of fluctuating renewables like wind, wave and solar power?

To answer this question, let us look more closely at two of the major changes that the large-scale deployment of renewable energy and more particularly wind energy, have already introduced in some countries and will produce in many other areas in the not so distant future.

In the first place, the power systems of the future will move away from the traditional pattern of centralised power plants towards more flexible decentralised structures. Smaller power plants in the form of individual wind turbines, or clusters of turbines, will be spread over larger areas in order to harvest the wind resource in places offering the best energy potential – balanced against economic viability, technical feasibility and environmental impact. At the same time, solar power panels will appear even in large cities.

The second change is inherent in the nature of the wind resource, which differs radically from conventional fossil fuels in two aspects. First, wind is highly nondispatchable, meaning that the output power of a wind farm can only be regulated (through curtailment) at the expense of lost power production. Second, wind is variable in both time and space, and can be predicted only with limited accuracy.

These changes imply that current practices for operating power grids and energy systems will most likely have to be revisited in order to integrate larger amounts of power from weather-dependent sources of energy. Coming back to our initial question, we can say without much doubt that the cornerstone of all the energy players' activities will be the use of advanced decision support systems capable of processing large quantities of information, and of delivering unique insights for managing power systems and mitigating the impact of weather variability. Such systems will include wind resource assessment and forecasting tools similar to those that we will present in the remainder of this chapter.

Advanced decision support systems form only a part of the solution for the large-scale decarbonisation of the energy system. Their effects will be magnified when used in combination with promising technologies such as energy storage systems and demand side management (control of electricity consumption) (Meibom *et al.*, 2013).

### Wind resource assessment

Investment decisions in wind power are driven to a large extent by the available wind resources at the sites under investigation. There are usually two steps to this. First, a wind atlas is made for a country or region (Petersen and Troen, 2012). Based on this wind speed map, an investor can find the most likely places to explore properly. But a wind farm resource study based on a wind atlas alone is not usually considered enough to obtain funding from the banks. The second step is therefore to take onsite measurements.

Best practice for measurements at the site of a projected wind farm is to use a meteorological mast as tall as the intended hub height of the turbines, and to measure wind speed at several heights including the World Meteorological Organisation standard height of 10 m above ground level. Measurements should be taken for at least a year, and preferably several years so as to account for climatological effects. Those measurements are then fed into a microscale wind flow model, which calculates the annual energy production (AEP) of the proposed wind farm, with some assumptions about turbine type, hub height and precise location. The flow models used vary significantly in accuracy and complexity. Linear flow models, which are essentially based on the mass consistency of the airflow, do well in gentle terrain without steep hills or large changes in roughness (like forest edges or land-sea borders). More computationally intensive models, such as those based on computational fluid dynamics (CFD), Reynolds Averaged Navier-Stokes (RANS) or large eddy simulation (LES) algorithms are required for complex terrain, increasing the calculation time by a factor of 1,000 or more.

The most recent example of a wind atlas is the Wind Atlas for South Africa (WASA; [www.wasaproject.info](http://www.wasaproject.info)).

In 2008 the government of South Africa, funded by the Danish Embassy, commissioned the most comprehensive wind atlas of the country to date. DTU Wind Energy, in conjunction with local partners, installed 10 tall met masts across the most populated areas of South Africa. Data collected over three years was fed into the Weather Research & Forecasting (WRF) model, which yielded a forecast spanning eight years with a 3 km horizontal resolution for the wind atlas (*Figure 27*), and a second 24-year forecast at 9 km resolution for variability studies and long-term corrections. This allowed good verification of the results against the measured data.

The method used to produce the wind atlas is based on a generalisation of wind climatologies derived from mesoscale modelling. This post-processing generalised method has been used extensively in a number of wind resource assessment studies, particularly within the KAMM-WASP method (see below). This is the first wind atlas study to use this generalisation on the WRF-model output.

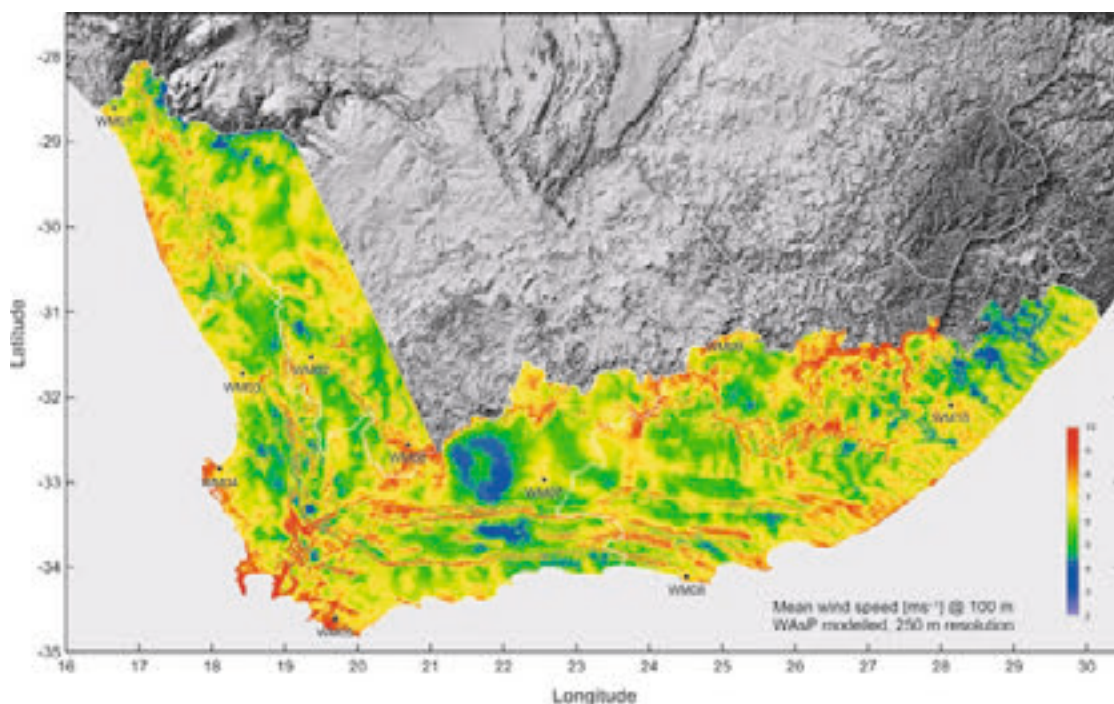
A speciality of the WASA is that it includes a detailed wind resource study produced by coupling the calculated regional wind fields to a microscale wind flow modelling program known as WASP ([www.wasp.dk](http://www.wasp.dk)). Since the 1980s, this flow model and associated software has been a standard way to calculate the wind resource at a specific turbine site in the vicinity of a meteorological mast. In the WASA, a full WASP analysis was done on a 250 m grid for the whole coloured region (*Figure 27*), so the siting of wind turbines can start directly from a calculated wind climate at any place covered by the wind atlas.

This was a considerable help to the fledgling South African wind power industry. According to the South African Wind Energy Association: “In 2011 there were eight wind turbines in the country but today five wind farms [are] in full operation, 15 more [are] under construction and a further seven [are] about to reach financial closure. Together, these would provide 1,983 MW of power to the national grid.” (IOL, 2014).

Figure 27 – Mean wind speed at 100 m above ground in most of South Africa.

Mean wind speed at 100 m above ground in most of South Africa, modelled by WASP.

The black dots represent the locations of the meteorological masts used for verification.



The next step in wind atlas work will be the new European Wind Atlas, which will address not only the wind resource in the target area but also such issues as the predictability of the wind, turbulence, the mechanical loads on wind turbines, the probability of icing, and other influences on the installation or operating cost of wind power plants. Additionally, the science in the calculation chain, especially at the interfaces between mesoscale and microscale modelling, will be investigated in more detail, and the whole flow modelling chain will be validated and assessed using a number of dedicated measurement campaigns.

### Wind power forecasting

Assessing the wind resource essentially consists of estimating the unconditional distribution of the wind and the corresponding power that can be generated from it. However, many operational problems involving wind energy require information on the dynamic behaviour of the wind, and hence its conditional distribution in space and time – especially in terms of the future output power of wind power plants.

A recent survey revealed that 94% of transmission system operators (TSOs) think that integrating significant amount of wind power into power systems will largely depend on the accuracy of wind power forecasts (Jones, 2010). Software for online wind power forecasting at both wind farm and regional levels has been used in Denmark since the mid-1990s (Madsen *et al.*, 1994).

Wind power forecasting systems are extensively used in countries that already have significant wind power penetration, such as Denmark, Spain and Germany, with respective levels of 33.2%, 16.3% and 10.8% (Wilkes and Moccia, 2013). These systems traditionally rely on both meteorological and statistical approaches. They use meteorological models to describe the physics of the atmosphere. Statistical models then take the meteorological forecasts as input to improve their calibration, converting wind speed forecasts to power forecasts. Finally, the programs quantify the inherent uncertainty of their deterministic forecasts.

It has been demonstrated that using several meteorological forecasts as input leads to significant

improvements in forecast accuracy. Nielsen *et al.* (2007) found that the use of two or more meteorological forecasts produced a 10–15% improvement in the accuracy of forecasts of wind power production for the Klim wind farm (*Figure 28*) in Denmark. The left panel shows the predictive performances of single meteorological forecasts while the right panels show their corresponding performance when these forecasts are combined 2 by 2 or 3 by 3. These forecasts are produced by three different models, namely the Deutscher Wetterdienst (DWD) model, the HIRLAM (HIR) model from the Danish Meteorological Institute, and the MM5 model which is the fifth generation of NCAR Mesoscale Model. The best results (that is, lowest RMS score) are obtained when 3 meteorological forecasts are combined. For an overview of the challenges in wind power forecasting from a physical perspective, we refer to Focken and Lange (2006). Likewise, Pinson (2013) discusses wind power forecasting challenges from a statistical perspective. In the remainder of this chapter we focus on some of the most important characteristics of wind power forecasts.

### Wind power forecast characteristics

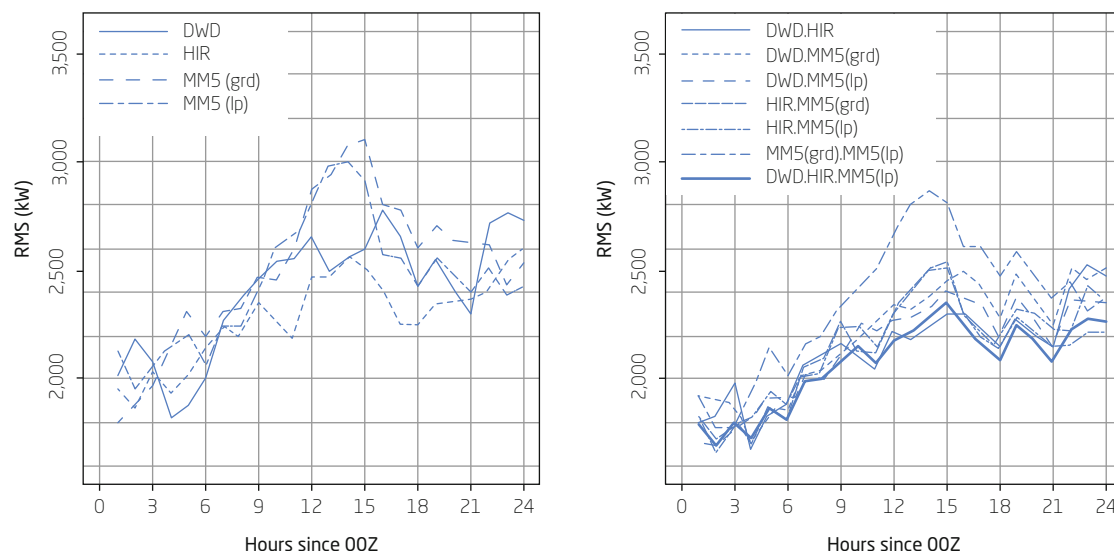
Different wind integration problems call for different types of wind power forecasts. More specifically, these forecasts should be generated with characteristics that meet the requirements specified by end-users (Nielsen *et al.*, 2011). These characteristics include the scale in time and space, the forecast lead time (often referred to as the forecast horizon), and the update frequency.

**Timescale:** Wind power developments have historically focused on methodologies for generating hourly wind power forecasts (Giebel *et al.*, 2011). This is most likely due to the structure of the electricity markets, which trade electricity over time units of one hour. However, experts in energy management have argued that increasing the scheduling frequency of electricity generation and delivery from hours to minutes would greatly facilitate the balancing of production and consumption (Energy GE, 2010). Grid operators agreed that a sub-hour approach would be helpful when handling large amounts of wind power in power systems (Jones, 2011). This calls for new approaches capable of capturing the intra-hour variability of wind power

Figure 28 – Forecasts for the Klim wind farm in Denmark.

All the forecasts were produced with WPPT (Wind Power Prediction Tool: [www.enfor.dk/products/wppt.html](http://www.enfor.dk/products/wppt.html)) but with different meteorological forecasts used as input.

(left) Forecasts from a single meteorological input. (right) Forecasts with various combinations of meteorological forecasts as input. The models used to generate the different meteorological forecasts were DWD (Deutscher Wetterdienst), HIRLAM (Danish Meteorological Institute) and MM5 (the fifth generation of the NCAR Mesoscale Model). The best forecast performance is seen when DWD, HIR and MM5 inputs are combined in the WPPT forecasting software.



generation, potentially through the use of new data sources such as weather radar observations (Trombe *et al.*, 2013).

**Frequency update:** The underlying philosophy in statistical forecasting is to use historical data to train models that then predict the future. As time passes, changes in several “hidden factors” influence the generation of wind power. One of these hidden factors is the response of the wind turbine fleet to the wind flow (i.e. the power curve), which changes over time as new turbines are added and other turbines grow old. It is also well known that dirty turbine blades can decrease production by up to 20%. Changes in the roughness of the surroundings (e.g. trees dropping their leaves) also require rapid updates to the forecasting models. In a context where the timely delivery of forecasts to end-users is crucial, it is essential to develop forecasting schemes that can be updated rapidly, without the need to repeat the time-consuming training stage. Such schemes can be set up through the use of adaptive and recursive estimation methods (Madsen, 2008; Møller *et al.*, 2008; Pinson, 2012).

**Horizon:** Wind is variable on a wide range of timescales, from minutes to years. Accurate wind power

forecasts are therefore needed over many different time horizons. Forecasts up to six hours ahead allow optimal management of reserve capacities in the event that one or more power plants fail to meet their scheduled production. Forecasts in the range 0–48 hours are needed to participate in electricity market auctions and dispatch the electricity produced. Forecasts on timescales of weeks and months are needed to plan maintenance of wind power plants and transmission lines.

#### From point to probabilistic forecasts

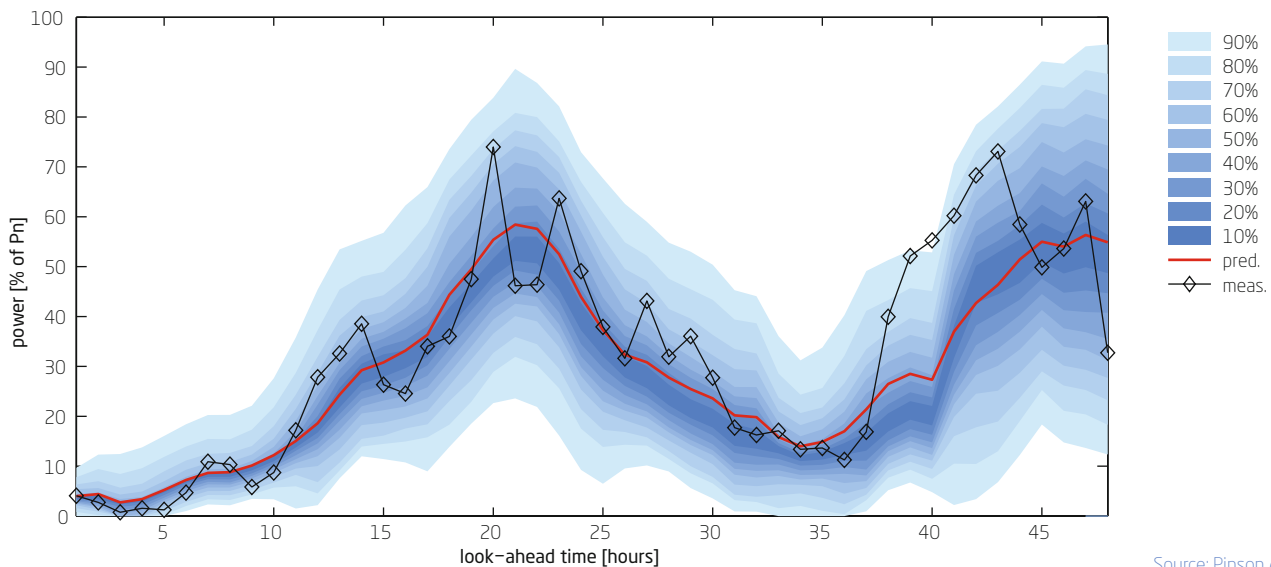
“Point forecasts” are single-valued: they specify only the expected or most likely value of the system under investigation. In wind energy there is a long tradition of using point forecasts for dispatching and trading activities, for instance (Giebel *et al.*, 2011).

However, such inputs are known to be suboptimal for many operational problems, since they only give a very limited account of what can happen in the future. Indeed, forecasts of stochastic processes – such as those that depend on the weather – are by nature uncertain.

The real value of a point forecast can therefore only be appraised when the forecast is presented



Figure 29 – Point and probabilistic forecasts of wind power generation versus measurements.



Source: Pinson *et al.*, 2007.

with information quantifying its uncertainty in the form of a predictive quantile, interval or even the full density distribution (Figure 29) (Pinson, 2013). Nowadays the focus is on new research areas such as probabilistic estimation frameworks based on stochastic differential equation (SDE) models (Møller *et al.*, 2013; Iversen *et al.*, 2014); models that can account for spatio-temporal correlations in wind power forecast errors in a probabilistic fashion (Tastu *et al.*, 2014a); and the integration of probabilistic forecasts into decision-making problems, particularly electricity markets (Morales *et al.*, 2014).

### From probabilistic to scenario forecasts

Probabilistic forecasts as illustrated in Figure 29 do not describe how prediction errors persist in time. A full description of this persistence is very important for applications containing start-stop or storage considerations, among others. Pinson *et al.*, 2009, and Nielsen *et al.*, 2011 demonstrated that neglecting the existence of this persistence could imply seriously wrong decisions on the size of a storage system.

The most advanced forecast product that is currently available for wind power prediction software, both in the technical literature and on the market, is what operations researchers call a scenario (Pinson, 2013).

A scenario is essentially a plausible conditional realisation of a stochastic process – describing, for instance, the power output of a particular wind farm over time.

In the same manner that the outcome of a random variable is a single value, the outcome of a stochastic process is a scenario: a series or time-indexed vector of values representing a potential time evolution of the stochastic process. An infinite number of scenarios is thus theoretically required to carry the full information – predictive densities, time dependence of forecast errors, etc. – about the stochastic process they represent.

The concept of a scenario can be easily extended to multivariate stochastic processes, when describing, for example, the power outputs of various geographically dispersed wind farms. In such a case, each scenario sampled from the multivariate stochastic process represents a plausible spatiotemporal evolution of the process. An example of such scenarios is given in Figure 30 for two regions of Denmark. Two different techniques are used for generating a set of 5 scenarios for lead times up to 43 hours ahead. The first technique does not take into account the spatio-temporal dependencies between the 2 regions whereas the second technique does. The resulting

sets of scenarios are more consistent in space and do not evolve as random walks when respecting spatiotemporal dependencies. Scenarios are also referred to by meteorologists as ensemble forecasts, and by forecasters as path-time trajectories.

Scenarios have been widely used by researchers and practitioners to model wind power. The reason for their well-deserved popularity is that the information contained in a good set of wind power scenarios can be fully exploited by techniques of optimisation under uncertainty, in particular by stochastic programming, to build advanced tools for operating and planning energy systems. This has spurred researchers to design tools to generate good scenario representations of the wind power stochastic process.

Alongside scenario generation tools, scenario reduction techniques have also been proposed. These aim to select a small subset of scenarios to render the associated stochastic programming problem computationally tractable, while retaining much of the information contained in the original much larger set (Morales *et al.*, 2014).

## Conclusion

More than 30 years of research on wind resource assessment and wind power forecasting have led to the application of advanced tools for supporting decisions in the development as well as the operation phase of wind energy projects, including the siting of future wind farms or trading wind energy on energy markets. Yet, many challenges remain in view of making wind energy more viable, cheaper and integrating larger amounts of wind power into power systems.

This chapter presented the future challenges for improving wind resource assessment and wind power forecasting tools. New and improved wind atlas is under development. They will integrate an increased number of factors such as wind predictability, loads of the wind turbines or even the probability of icing. As for the wind power forecasting tools, the way forward is to develop better probabilistic forecasts, and develop solutions for integrating this type of information into decision-making problems.

Figure 30 – Scenarios generated for two areas in Denmark.

Scenarios generated for two areas in Denmark; (left) ignoring spatiotemporal effects; (right) taking these effects into account.

Source: Tastu *et al.*, 2014b.

